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A cross-country evaluation of environmental performance: Is there a convergence-divergence pattern in technology gaps?

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ABSTRACT

A balanced panel of 103 countries for the period 1995–2011 is introduced into a metafrontier framework to gain insight into the idiosyncratic performance of countries in two distinct groups — developed (Annex I) countries and developing (non-Annex I) countries. We measure efficiency using a generalized directional distance function model suitable for dealing with anthropogenic emissions. The measurement of efficiency and technology gaps takes into account the group-specific heterogeneity. Moreover, we examine the convergence-divergence hypothesis for the technology gaps defined for each period. Our findings reveal significant patterns between the groups and among countries.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC, 2007) has assessed that over the last 50 years, global warming has been caused by anthropogenic greenhouse gas (GHG) emissions. The impact of GHGs on climate change has been top of the agenda of, and is considered the leading issue for many governments, organizations, economists, researchers, and scholars, because it threatens countries' sustainable development (Tol, 2009; Weitzman, 2009). The significance of this problem is apparent from cases such as the signing of the Kyoto Agreement in 1997, followed by efforts in Copenhagen and Cancun (2010), Durban and Doha (2011), Warsaw (2013), and most recently, in Paris (2015) to reach an international agreement aimed at reducing GHG emissions. In the face of climate change repercussions, many countries have devoted a large portion of their resources to designing and implementing solutions that mitigate GHGs in order to achieve a satisfactory level of sustainable development. Others (headed by the United States) have insisted on a more voluntary orientation. Furthermore, it is true that Kyoto climate policies place more attention and emphasis on the reduction of global emissions in order to mitigate climate change (Lin et al., 2013).

The Kyoto Protocol was negotiated in 1997 during the Third Conference of the Parties to the United Nations Framework Convention of Climate Change. During its sessions, there were discussions on the reduction levels of GHGs, most notably CO_2 from fossil fuel combustion, for developed (Annex I) and developing (non-Annex I) countries in an international agreement framework (Den Elzen & Höhne, 2008). The distinction between Annex I countries and non-Annex I countries is strongly embedded in the climate regime, and plays a crucial role in the 1992 United Nations Framework Convention on Climate Change as well as in the Kyoto Protocol. The principle of common but differentiated responsibilities and respective capabilities launched in 1992, and followed in subsequent treaties, clearly separates the developed from the developing countries and refers to different obligations and responsibilities according to their technology status.

Given that the world's economies are linked by international trade and capital flows, emissions abatement by Annex I economies may impact the trade, carbon leakage, and transfer and diffusion of energy-efficient technologies to non-Annex I economies (Den Elzen & De Moor, 2002). A further caveat, from the stance of economic theory, considers large economic adjustment costs to Annex I countries (Böhringer & Vogt, 2003) or possible policies (e.g., preferential tariffs reductions) on their compensation (Babiker et al., 2000). Furthermore, some studies report that recent Kyoto modifications, including the U.S. decision not to ratify the Protocol and the recent outcomes of the Bonn and Marrakech Conferences of the Parties, regard climate policies as business as usual, thus bringing into question its economic and environmental impacts for the countries participating in this commitment (Böhringer & Vogt, 2003, 2004).

The level of the ambition to reduce emissions of Annex I and non-Annex I countries under the Kyoto agreement is one of the

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most important aspects of current climate negotiations. Although there have been many attempts to convince the non-Annex I group to ratify the agreement, several political, institutional, and economic barriers have hindered them (Calbick & Gunton, 2014).[1] Thus, the clear distinction between Annex I and non-Annex I countries provides a significant opportunity for engineers, economists, scholars, and politicians to examine the negative impact of human activity, in terms of pollution equivalents, even at a country level. There is growing interest in incorporating undesirable outputs in the production function under the different technological regimes. This has yielded numerous published articles (Zhang & Choi, 2014), and has introduced several methods for handling the two types of outputs (i.e. desirable and undesirable) asymmetrically (e.g., Tone, 2001; Cheng & Zervopoulos, 2014).

A common characteristic of these studies is that they operate under the assumption of technological isolation (Tsekouras et al., 2016), examining a rather homogeneous group (Feroz et al., 2009; Halkos & Tzeremes, 2014). They may also adopt a metafrontier production function in a "mechanistic" way, creating groups according to specific criteria, while ignoring their technological status (Kounetas, 2015). The introduction of the metafrontier production function (Battese et al., 2004) allows technological heterogeneity to be incorporated in productive efficiency analyses, thus relaxing the restrictive technological isolation conditions. In the framework of technological heterogeneity, any positive influence of technological spillovers from domestic mitigation strategies onto environmental performance may be eliminated if the production units are locked in, or if they exhibit path dependence in the evolution of their environmental performance (Tsekouras et al., 2016). Thus, technology gap estimation with respect to Annex I and non-Annex I countries accounts for the impact of factors associated with the idiosyncrasies that emanate from a country's technologies.

Technology heterogeneity (Dosi & Nelson, 2010) is based on the application of environmentally friendly and mitigation technologies, while the corresponding technology gaps allow for country-specific economic, social, but mainly technology differentials to affect their performance. Moreover, this approach serves as an appropriate index for the evolution of countries' performance by considering simultaneously the status of production and their evolution of technology within a particular country and a world technology.

In this study, we introduce a generalized directional distance function (Cheng & Zervopoulos, 2014) in a metafrontier framework and use it in conjunction with distributional dynamics approach to allow a concurrent examination of the following: (a) efficiency differences in the environmental performance of countries operating under two distinct technological regimes; (b) any inter-linkages and flows between the two heterogeneous technologies and, more specifically, spillover effects to non-Annex I countries; and (c) the convergence hypothesis for technology gaps in the set of countries examined over the period 1995–2011. This analytical framework is applied to 103 countries for the review period (1995–2011), revealing interesting patterns of environmental performance that have not been identified by previous studies on productive efficiency.

The remainder of this paper is structured as follows. Section 2 reviews the literature on directional distance functions (DDFs) and metafrontier analysis. Section 3 presents the methodology. Section 4 describes the selection of the input and output variables, and Section 5 discusses the results of the empirical analysis. Lastly, Section 6 concludes the paper.

[1] In Article 2 of the Agreement of Technology Transfer, financial support for the establishment of environment-friendly technologies and funding for technology are the essential elements for the implementation of the agreement.

2. Review of the literature

In efficiency and productivity analysis, DDFs have also become popular because most production processes generate undesirable output(s) as byproduct(s) (e.g., CO_2 emissions by firms, or mortality rates for health systems). The main reason for this increased popularity is the ability of a DDF to increase good outputs, while reducing bad outputs because the production process of every entity has economic, environmental, and social outputs (Färe & Grosskopf, 2000; Färe et al., 2005; Zhang et al., 2013). In this context, many empirical studies have used DDF to investigate the performance of individual decision-making units (DMUs). Previous studies have applied DDFs to measure energy efficiency (Zhou et al., 2012; Zhang et al., 2013), productive efficiency (Camarero et al., 2008; Kumar & Khanna, 2009; Kounetas, 2015), sustainability performance (Zhang et al., 2013), and eco-efficiency (Kuosmanen and Kortelainenn, 2005; Färe et al., 2007; Oggioni et al., 2011; Picazo-Tadeo et al., 2012).[2]

In terms of the methodological approaches that have been used to estimate the above-mentioned indices, the literature identifies three groups, based on the studies' frameworks. The first group contains transformations of conventional DEA models, including hyperbolic distance functions (Färe et al., 1989), radial measures (Chambers et al., 1996), and non-radial measures. The second group concerns modifications of the slack-based measures (Tone, 2001), while the third group includes several modifications of the directional distance function (Chung et al., 1997).

Many studies have incorporated DDFs to measure the energy and environmental performance of DMUs. As mentioned above, the radial nature of a DDF has motivated researchers to develop non-radial measures. For instance, Färe and Grosskopf (2010) and Zhou et al. (2012) extend it in a non-radial model, and Mahlberg et al. (2011) proposed a non-radial Luenberger indicator. Extending the DDF, Zhang et al. (2013) and Zhou et al. (2006) developed several slack-based measures for environmental performance. Then, Fukuyama and Weber (2009) proposed a slack-based measure of efficiency, combining the ideas of a DDF and the slack-based measures. In addition, Taskin and Zaim (2001) and Cuesta et al. (2009) developed a hyperbolic efficiency measure. Using DDFs, Fukuyama et al. (2011) and Barros et al. (2012) proposed slack-based measures and a weighted Russell DDF, respectively. Sueyoshi and Goto (2010) proposed a range-adjusted measure model for US coal-fired power plants. Finally, Färe and Grosskopf (2010) and Cheng and Zervopoulos (2014) put forth a generalized non-radial DDF, and Zhang and Choi (2014) presented a sequential generalized directional distance function.

However, very few studies have considered potential technology heterogeneity. Oh (2010), using a Malmquist–Luenberg productivity index, incorporated group heterogeneity. In addition, Kounetas (2015), Chiu et al. (2012), and Lin et al. (2013) measured technology gaps and environmental efficiency technology gaps, exploiting the scarcity of similar studies under the presence of heterogeneity.

3. Methodology

Our methodological framework is developed in two interconnected stages. In the first stage, we present the theoretical and methodological underpinnings of the estimation of the generalized directional distance function. Here, we also discuss the expansion in a metafrontier framework, presenting the theoretical base for its inclusion. In the second stage, we present the theory on the convergence hypothesis using distributional dynamics approach that adopts a Markov chain and stochastic kernel.

[2] Zhang and Choi (2014) present a comprehensive review of the literature on DDFs related to environmental and energy studies.

3.1. Definitions, notation, and technological gaps

The inputs $x = (x_1, \ldots, x_m) \in \mathbb{R}^m_+$ are used to produce desirable outputs $y = (y_1, \ldots, y_s) \in \mathbb{R}^s_+$ and undesirable outputs $b = (b_1, \ldots, b_p) \in \mathbb{R}^l_+$ (e.g., CO_2 emissions). In this context, the technology is described as follows:

$$T(x) = \{(y, b) : x \text{ can produce } (y, b)\} \tag{1}$$

where $T \subset \mathbb{R}^m_+ \times \mathbb{R}^s_+ \times \mathbb{R}^l_+$, which represents the input–desirable output–undesirable output bundles that are technologically achievable.

The desirable outputs (y) are produced together with the undesirable outputs (b), which is modeled as follows:

$$\text{if } (y, b) \in T(x) \text{ and } b = 0 \text{ then } y = 0 \tag{2}$$

The technology satisfies the following assumptions: (a) closedness, (b) free disposability of inputs and desirable outputs: $\forall\ (x, y) \in T,\ \text{if } x' \geq x \text{ and } y' \leq y \text{ then } (x', y') \in T$, (c) weak disposability of undesirable outputs: $\forall\ (x, b) \in T \Rightarrow (x, \mu b) \in T\ \forall\ \mu \geq 1$, (d) no free lunch: if $(x, y, b) \in T$ and $x = 0$ then $y = 0$ and $b = 0$, (e) doing nothing is feasible: $(0, 0, 0) \in T$, and (f) convexity (Färe et al., 1994).

The technology is described by the following directional distance function (DDF):

$$\vec{D}_T(x, y, b; g_x, g_y, g_b) = \sup\{\beta : (x - \beta g_x, y + \beta g_y, b + \beta g_b) \in T(x, y, b)\} \tag{3}$$

where β denotes inefficiency and the non-zero $g = (g_x > 0, g_y > 0, g_b < 0)$ expresses the direction vector of the inputs, desirable outputs, and undesirable outputs, respectively. Expression (3) reflects a simultaneous reduction in inputs, an increase in desirable outputs, and a decrease in undesirable outputs. In the case of non-orientation, Chen et al. (2011) obtained efficiency from

$$min \frac{1 - \beta}{1 + \beta} \tag{4}$$

as the DDF yields inefficiency (β).

In this study, a generalized directional distance function (GDDF) is applied to measure environmental efficiency, as proposed by Cheng and Zervopoulos (2014). According to this GDDF, which is based on expression (3) and satisfies the technology assumptions, efficiency (θ) is measured ex-post as

$$min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \beta g_i / x_{io}}{1 + \frac{1}{s+l}\left(\sum_{r=1}^{s} \beta g_r / y_{ro} + \sum_{\eta=1}^{l} \beta g_\eta / b_{\eta o}\right)}, \tag{5}$$

where $\beta g_i / x_{io}$ expresses the proportion of the reduction in inputs, and $\beta g_r / y_{ro}$ and $\beta g_\eta / b_{\eta o}$ indicate the proportion of the increase and decrease in desirable and undesirable outputs, respectively. The efficiency measures obtained from this GDDF are units invariant; monotone; translation invariant, provided that the variable returns to scale (VRS) technology applies; and reference-set invariant (Tone, 2001; Färe & Grosskopf, 2010).

Like the conventional DDF (expression (3)), the GDDF produces efficiency scores (θ_j) consistent with those obtained from radial models when the input and desirable and undesirable output vectors are set equal to the inputs and desirable and undesirable outputs, respectively, of the reference DMU (i.e., $g_x = x_o,\ g_y = y_o,\ g_b = -b_o$). A drawback of the DDF, which is overcome by the GDDF, is that it measures inefficiency (β). The inefficiency obtained from the DDF is not an appropriate measure as it does not always lie within the interval of zero to one. In Tables[3] A1 and A2 in the Electronic Supplement, the inefficiency (β) obtained from the DDF respects the interval of zero to one only when $g_x = x_o,\ g_y = y_o$ and $g_b = -b_o$. In the remaining two cases, where (a) $g_x = 1,\ g_y = 1,\ g_b = -1$, and (b) $g_x = 2,\ g_y = 2,\ g_b = -2$, inefficiency cannot be interpreted as it may exceed unity. In the same tables, it is evident that the GDDF yields efficiency scores (expression (5)). An advantage of the GDDF is that the efficiency scores obtained are independent of the length of the direction vectors. In Tables A1 and A2, the GDDF efficiency scores are the same in both cases where (a) $g_x = 1,\ g_y = 1,\ g_b = -1$, and (b) $g_x = 2,\ g_y = 2,\ g_b = -2$.

The slacks-based measure (SBM) put forth by Tone (2001) is another approach to assess efficiency (θ) in the presence of undesirable outputs. In Tables A1 and A2, we present the efficiency scores of Annex I and non-Annex I countries, respectively, obtained from a modified SBM developed by Fukuyama and Weber (2009, 2010). In both tables, all inefficient countries ($\theta_j < 1$) are assigned scores lower than those measured by the radial, DDF and GDDF (when the direction vectors are set equal to the input and output values of the reference DMU). In addition, SBM is not appropriate for handling asymmetrically desirable and undesirable outputs. In Table A3, in the Electronic Supplement, the cases where the SBM fails to define minimal inputs while maximizing desirable outputs and minimizing undesirable outputs are shown in grey. In Table A3, where the sample consists of 64 non-Annex I countries, the SBM fails in 35 cases (e.g. Georgia – GEO, Ghana – GHA, Indonesia – IDN).

In the case where multiple technologies (γ distinct technologies, where $\gamma = 1, \ldots, \Gamma$) are present, the input–desirable output–undesirable output sets are grouped into γ technologically feasible sets ($T^1, T^2, \ldots, T^\Gamma$). The collection of all feasible input-output combinations of the operational units (i.e., countries) construct the smallest convex set, known as the meta-technology set, and denoted by T^{meta} (Battese & Rao, 2002; Battese et al., 2004; O'Donnell et al., 2008). The meta-technology set is modeled as:

$$T^{meta}(x) = \{(y, b) : x \text{ can produce } (y, b)\} \tag{6}$$

and the group-specific technology set is described as:

$$T^\gamma(x) = \{(y, b) : x \text{ used by operational units in group } \gamma \text{ can produce } (y, b)\} \tag{7}$$

Hence, $T^{meta}(x) = \{T^1(x) \cup T^2(x) \cup \ldots \cup T(x)^\Gamma\}$.

By introducing the GDDF (Cheng & Zervopoulos, 2014) into the meta-technology framework, we measure the meta-efficiency and group-specific efficiency scores as follows:

$$\begin{aligned}
&\vec{D}_{T^{meta}}(x^\gamma, y^\gamma, b^\gamma; g_x, g_y, g_b) \\
&\quad = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \beta^{meta} g_i / x^\gamma_{io}}{1 + \frac{1}{s+l}\left(\sum_{r=1}^{s} \beta^{meta} g_r / y^\gamma_{ro} + \sum_{\eta=1}^{l} \beta^{meta} g_\eta / b^\gamma_{\eta o}\right)} \\
&s.t.\quad \sum_{\gamma=1}^{\Gamma}\sum_{j=1}^{n} \lambda^\gamma_j x^\gamma_{ij} \leq x^\gamma_{io} - \beta^{meta} g_x \quad i = 1, \ldots, m \\
&\quad \sum_{\gamma=1}^{\Gamma}\sum_{j=1}^{n} \lambda^\gamma_j y^\gamma_{rj} \geq y^\gamma_{ro} + \beta^{meta} g_y \quad r = 1, \ldots, s \\
&\quad \sum_{\gamma=1}^{\Gamma}\sum_{j=1}^{n} \lambda^\gamma_j b^\gamma_{\eta j} = b^\gamma_{\eta o} + \beta^{meta} g_b \quad \eta = 1, \ldots, l \\
&\quad \sum_{\gamma=1}^{\Gamma}\sum_{j=1}^{n} \lambda^\gamma_j = 1 \\
&\quad \lambda^\gamma_j \geq 0
\end{aligned} \tag{8}$$

[3] The scores presented in Tables A1 and A2 are obtained from the data sets discussed in Section 4 and used in Section 5 (empirical analysis) of this study.

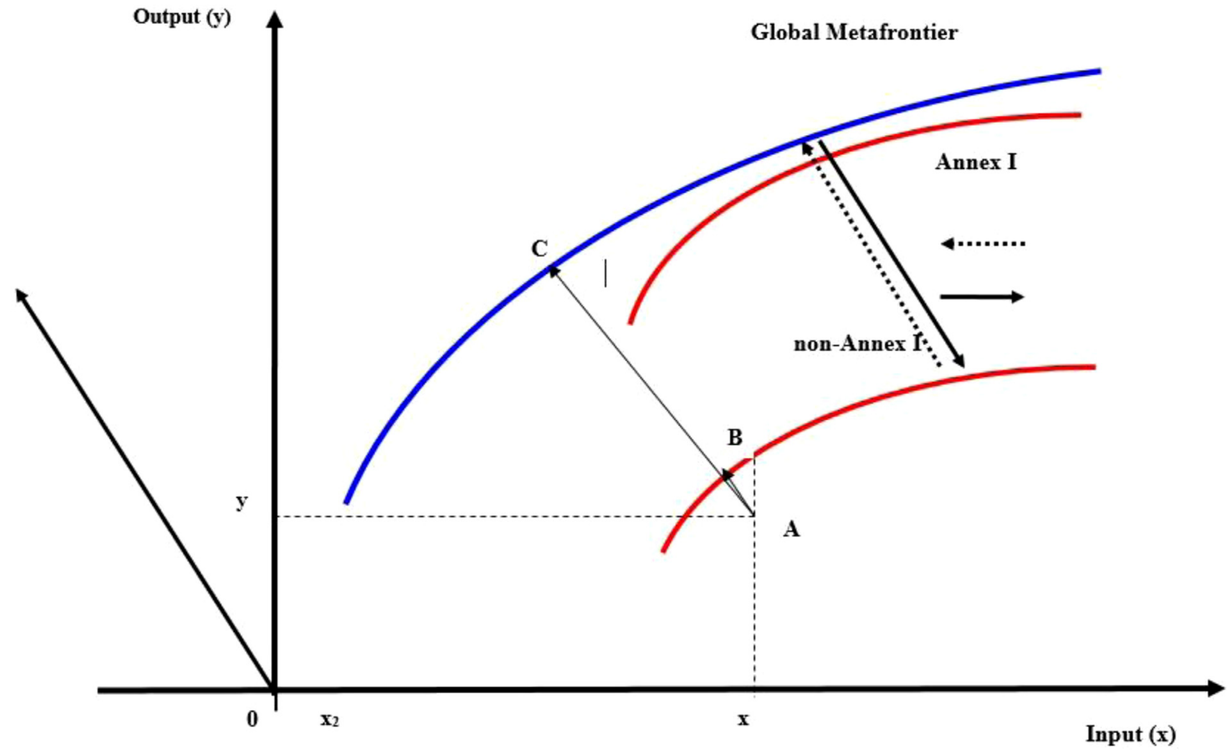


Fig. 1. Meta-frontier, individual frontiers, for the single input–single output case.

$$\vec{D}_{T^\gamma}(x^\gamma, y^\gamma, b^\gamma; g_x, g_y, g_b) = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\beta^\gamma g_i/x_{io}^\gamma}{1 + \frac{1}{s+l}\left(\sum_{r=1}^{s}\beta^\gamma g_r/y_{ro}^\gamma + \sum_{\eta=1}^{l}\beta^\gamma g_\eta/b_{\eta o}^\gamma\right)}$$

$$s.t. \quad \sum_{j=1}^{n} \upsilon_j^\gamma x_{ij}^\gamma \leq x_{io}^\gamma - \beta^\gamma g_x \; i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \upsilon_j^\gamma y_{rj}^\gamma \geq y_{ro}^\gamma + \beta^\gamma g_y \; r = 1, \ldots, s$$

$$\sum_{j=1}^{n} \upsilon_j^\gamma b_{\eta j}^\gamma = b_{\eta o}^\gamma + \beta^\gamma g_b \; \eta = 1, \ldots, l$$

$$\sum_{j=1}^{n} \upsilon_j^\gamma = 1$$

$$\upsilon_j^\gamma \geq 0, \; \gamma = 1, \ldots, \Gamma \qquad (9)$$

where λ_j^γ and υ_j^γ represent the optimal weights assigned to the inputs and outputs. In our case, $g_x = (1, 1, 1)$, $g_y = (1)$ and $g_b = (-1)$, because our data set consists of three inputs, one desirable output, and one undesirable output (see Fig. 1).

Using programs (8) and (9), we can calculate the technology gap ratio (Battese et al., 2004) or the reciprocal relationship of the meta-technology ratio (MTR) (O'Donnell et al., 2008).

$$0 < \mathrm{MTR}(x, y, b) = \frac{\mathrm{MTE}(x, y, b)}{\mathrm{TE}(x, y, b)} = \frac{\dfrac{1-\frac{1}{m}\sum_{i=1}^{m}\beta^{meta}g_i/x_{io}^\gamma}{1+\frac{1}{s+l}\left(\sum_{r=1}^{s}\beta^{meta}g_r/y_{ro}^\gamma+\sum_{\eta=1}^{l}\beta^{meta}g_\eta/b_{\eta o}^\gamma\right)}}{\dfrac{1-\frac{1}{m}\sum_{i=1}^{m}\beta^\gamma g_i/x_{io}^\gamma}{1+\frac{1}{s+l}\left(\sum_{r=1}^{s}\beta^\gamma g_r/y_{ro}^\gamma+\sum_{\eta=1}^{l}\beta^\gamma g_\eta/b_{\eta o}^\gamma\right)}} \leq 1 \qquad (10)$$

where MTE expresses the technical efficiency of an operational unit with respect to the meta-technology, and TE represents the technical efficiency of an operational unit with respect to the γ group frontier.

The metafrontier framework provides benchmarking for all operational units independently of the group-specific frontier to which each unit belongs. As a result, drawing on the technology heterogeneity concept, we can attribute differences captured by technology gaps to the following: (a) the structure of national markets, (b) national regulations and policies, (c) cultural profiles and legal and institutional frameworks (Halkos & Tzeremes, 2011), (d) available resource endowments, (e) economic infrastructure, (f) characteristics of the physical, social, and economic environment in which production takes place (O'Donnell et al., 2008; Kounetas et al., 2009), and (g) knowledge characteristics and strategic orientation (Kontolaimou & Tsekouras, 2010). An MTR value closer to unity indicates less technology heterogeneity, while a value closer to zero denotes greater technology heterogeneity.

In this study, the metafrontier approach has been adopted since (a) developed countries (Annex I) are responsible for the majority of greenhouse gas emissions and are the ones that develop, finance, access and transfer environmentally sound technologies, (b) developing countries (non-Annex I) face significant barriers (e.g., high costs, knowledge diffusion) trying to develop or acquire these technologies in order to catch up with Annex I countries.

In addition to the identification of technology heterogeneity, the meta-technology framework facilitates the measurement of technology gaps. Chiu et al. (2012) defined technology gap inefficiency as the distance between the individual frontier and the metafrontier. The technology gap is obtained as follows:

$$\mathrm{TG}(x, y, b) = \mathrm{TE} \times (1 - \mathrm{MTR}(x, y, b)) \qquad (11)$$

We present a graphical analysis (see Fig. 1) of the global metafrontier and the two individual frontiers for the output-oriented framework. At a given input (x) and output (y), country A under the non-Annex I technology consists of three components. First, the technical inefficiency (GDDF relative to the group frontier) between points A and B, the meta-technical inefficiency between points A and C (GDDF relative to the metafrontier), and the technology gap.

3.2. The technology gaps' stochastic convergence hypothesis

There are three main threads of analysis in the literature. Within the first thread (i.e., the time series approach), a variety of methods has been adopted, including the pairwise convergence (Pesaran, 2007) or the stochastic convergence approach (Carlino and Mills, 1993). The second thread refers to the well-known concepts of beta- and sigma-convergence (Barro & Sala-i-Martin, 1991; Mankiw et al., 1992), while the third adopts distributional dynamics.

In this study, we adopt the distributional dynamics approach. The main reason for this choice is that we want to directly examine the evolution of the cross-sectional distribution using stochastic kernels to describe both the change in its external shape and the intra-distribution dynamics, which will allow us to investige the possible formation of clubs concerning technological gaps. Moreover, in line with the arguments of Quah (1993; 1996b, c) and Darlauf et al. (2005), this study uses distributional dynamics that adopt a Markov chain as one of the alternatives to beta-, and sigma- and gamma-convergence (beta- and sigma-convergence estimates appear in the Electronic Supplement; Tables A10 and A11). Non-parametric modeling allows us to study the dynamics of the entire distribution of technology gaps as opposed to an average behavior as is commonly done in most time series studies. Furthermore, one of the most significant features is that equilibrium is stochastic and not deterministic as is assumed in the pairwise and beta-, sigma- and gamma-convergence approaches. The distributional dynamics approach embodies notions of increasing returns associated with endogenous growth theory (Quah, 1996b) while allowing us to consider neoclassical assumptions in a more liberal way. Finally, the distributional dynamics approach is seen to accord with reality, where countries move between energy and environmental levels under the presence of shocks (Fingleton, 1999). In addition, this approach is suitable when the analysis is limited to a "homogeneous" set of economies (Barro et al., 1991; Barro & Sala-i-Martin, 1991), allowing for heterogeneity across them (Bimonte, 2009).

In practice, we can consider a technology gap[4] as a continuous-time stochastic process $\{\Psi(t),\ t \geq 0\}$, and assume that each stochastic process is a continuous-time Markov chain. Each Ψ satisfies the Markovian property $\text{Prob}(\Psi_{t+\tau} \in A | \Psi_j,\ j \leq t;\ \Psi = \psi) = \text{Prob}^{\tau}(\psi, A)$ with $A \subseteq E \subseteq \mathbb{R}$, where E is the space state of Ψ.

The empirical estimate of the marginal probability density function of ψ is given by:

$$\begin{aligned}\hat{f}(\psi) &= \int_{-\infty}^{+\infty} \hat{f}(\psi, \omega)\mathrm{d}\omega \\ &= \frac{1}{n}\sum_{j=1}^{n} \frac{1}{h_\psi\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\psi-\psi_j}{h_\psi}\right)^2} \int_{-\infty}^{+\infty} \frac{1}{h_\omega\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\omega-\omega_j}{h_\omega}\right)^2}\mathrm{d}\omega \\ &= \frac{1}{n}\sum_{j=1}^{n} \frac{1}{h_\psi\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\psi-\psi_j}{h_\psi}\right)^2} \end{aligned} \tag{12}$$

where the joint distribution $f(\psi, \omega)$ is obtained using a product of the Gaussian kernel K (Fotopoulos, 2006):

$$\begin{aligned}\hat{f}(\psi, \omega) &= \frac{1}{n}\sum_{j=1}^{n} \frac{1}{h_\psi\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\psi-\psi_j}{h_\psi}\right)^2} \frac{1}{h_\omega\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\omega-\omega_j}{h_\omega}\right)^2} \\ &= \frac{1}{n}\sum_{j=1}^{n} \frac{1}{h_\psi} K\left(\frac{\psi-\psi_j}{h_\psi}\right) \frac{1}{h_\omega} K\left(\frac{\omega-\omega_j}{h_\omega}\right) \end{aligned} \tag{13}$$

[4] For clarity and presentation reasons we denote a technology gap as Ψ.

where h_ψ and h_ω are bandwidths, calculated using the direct plug method, applied separately in each dimension. Thus, a nonparametric estimation of the stochastic kernel[5] is given by:

$$\hat{f}_\tau(\omega|\psi) = \frac{\hat{f}(\omega, \psi)}{\hat{f}(\psi)} \tag{14}$$

The stochastic kernel may be interpreted as a transition matrix with a continuum of rows and columns. Let the time interval be of length τ. Then, the relationship between the two distributions over τ can be written as:

$$f_{t+\tau}(\omega) = \int_{-\infty}^{+\infty} f_\tau(\omega|\psi) f_t(\psi)\mathrm{d}\psi \tag{15}$$

Following the approach developed by Johnson (2000 and 2005) and Fotopoulos (2006), the long-run ergodic distribution is found as the solution to:

$$f_\infty(\omega) = \int_{-\infty}^{+\infty} f_\tau(\omega|\psi) f_\infty(\psi)\mathrm{d}\psi \tag{16}$$

One way to overcome this problem is to use a discretization of the time interval $[\alpha, \delta]$ by partitioning it into n non-overlapping subintervals. Then, it is possible to estimate $f_\tau(z_j|\psi_\upsilon)$, where $\upsilon = 1, \ldots, n$, with z_j, ψ_υ as midpoints of these subintervals. If $p_{\upsilon j} = f_\tau(z_j|\psi_\upsilon)\frac{\delta-\alpha}{n} (\geq 0)$ are defined and n is sufficiently large (which leads to $\sum_{j=1}^{n} f_\tau(z_j|\psi)\frac{\delta-\alpha}{n} \approx 1$), then the $n \times n$ matrix $\boldsymbol{P} = \{p_{\upsilon j}\}$ has the same structure as a transition probabilities matrix, and $\{p_{\upsilon j}\}_{j=1}^{n}$ may be seen as the conditional probability mass function. The ergodic density is evaluated as $f_\infty(\omega) = \zeta | \frac{\delta-\alpha}{n}$, where ζ is the rescaled (unit sum) left eigenvector corresponding to the unity eigenvalue (and the largest value) of the matrix $\boldsymbol{P}$.

4. Data sources and variable definitions

To investigate the issues surrounding our main research question we devised a unique data set by employing and matching distinct, but complementary, information sources. The resulting data set is a balanced panel consisting of 103 countries for the period 1995–2011, and our final panel dimension comprises 1751 observations. Note that our sample is affected by the events of the global financial crisis from August 2007 onwards, but also covers the period before and after Kyoto's implementation. Furthermore, the sample period was chosen purely based on the availability of key variables, some of which become unavailable after 1995.

In order to estimate productive efficiency with respect to each country frontier and to the specific metafrontier, we employ a multi-input–single-desirable output–single-undesirable output data set. More specifically, we approximate the output variable (Y) using the gross value added of each industry as the desirable output, and CO_2 emissions in metric tons (Mt) as the undesirable output. As inputs, we include the following: (a) capital stock (C) (in million dollars); (b) labor (L), captured by the total hours worked by employees; and (c) total energy consumption (E), measured in million tons (Mt) of oil equivalent. Table 1 provides basic descriptive statistics for each variable.

As already mentioned, the data are the result of combining several sources of information. The data on gross value added (Y) and total hours worked by employees (L) are taken from the World

[5] In general, the characteristics of the kernel function and bandwidths influence the quality of the density estimation. Different kernel alternatives may be used (Silverman, 1986; Wand & Jones, 1995). Since the kernel estimator is not very sensitive to a choice of K, a Gaussian kernel has been used (Magrini, 2007). Moreover, the mean integrated squared error (MISE) is minimized by a multivariate standard normal density over the class of product kernels (Pagan & Ullah, 1999).

Table 1
Descriptive statistics by type of agreement and variable (1995–2011).

Variables (Units of measurement)	Annex I	Non-Annex I	All
C (million \$)	2,424,502.7 (6,135,338.9)	1,061,657.0 (3,140,601.1)	1,577,685.9 (4,561,071.4)
L (million hours)	12.4 (24.1)	31.2 (104.3)	24.1 (84.1)
E (million tons of oil equivalent)	125.3 (356.0)	73.5 (222.8)	93.1 (281.8)
Y (million \$)	761,483.4 (1,938,420.5)	345,615.7 (976,065.3)	503,080.2 (1,433,135.1)
CO_2 (million \$)	307.3 (889.9)	185.2 (669.2)	231.4 (762.4)

Note 1. Numbers indicate the mean value while parentheses correspond to the standard deviation.
Note 2. All values are in constant 2005 prices.

Bank database (World Bank Developing Indicators). The capital (C) was obtained from the OECD Structural Analysis Database. For the CO_2 emissions variable (CO_2), we used emissions linked with energy combustion expressed in metric tons. The source of the CO_2 emissions data was the Enerdata-Odyssey database. Regarding the energy consumption variable (E), we used total primary energy supply (TPES), in units of tons of oil equivalent per thousand purchasing price parity (PPP) USD from International Energy Agency's (IEA) data series. TPES accounts for all energy consumed within a country, and is comprised of production imports excluding exports, international marine bunkers and international aviation bunkers (Kounetas, 2018). TPES adjusts for the energy consumed in producing electricity, and is different from the energy delivered (Liddle, 2010; Jacob et al., 2012; Kounetas, 2018).

Finally, the data on capital were acquired from the OECD Structural Analysis and World Bank databases. The GDP deflators used to convert the prices to constant 2005 prices are specific to each country. Note that the distinction between the two frontiers (Annex I and non-Annex I) has held since the Kyoto protocol.

5. Empirical results and discussion

The presentation and discussion of the empirical results follows the same two-stage structure as that of the methodology section. The country-specific efficiency scores for the two groups are first presented and discussed. Then, the meta-technology efficiency scores, meta-technology ratios, and technology gaps that arise in the context of the metafrontier are used to examine our hypothesis. Lastly, the results of the estimation of the stochastic kernel for the technology gaps are discussed.

5.1. Efficiency, meta-technology ratios, and technology gap estimates

Productive efficiency scores with respect to a specific technology and meta-technology, the associated meta-technology ratios, and the technology gaps are estimated for the 103 countries in each of the 17 years. Note that both the productive efficiency and the technology gap estimations are grounded on a cross-section basis, estimated separately for each year in the sample, denoting an individual production set. Therefore, the values of the estimated productive efficiency and technology gap for each country encompass two dynamic factors. The first is the change of the distance from the (meta-)frontier, and the second is the movement outwards (technical change) or inwards (technical regression) of the metafrontier itself (see Fig. 1). Thus, the estimated time-series for the efficiency and technology gaps reflect the diachronic evolution of the environmental performance of a country, considering technological developments either in the industry-specific frontier or in the meta-technology.

The mean group-specific efficiencies, meta-efficiencies, technology gaps and standard deviations of these measures for Annex I and non-Annex I countries are shown in Table 2. Detailed results for all these measures are available in Tables A4–A7 in the Electronic Supplement.

According to Table 2, the mean meta-efficiency for both the Annex I and non-Annex I countries is 0.828. This implies that the inputs employed by the 103 sample countries have the potential to increase the desirable output (i.e., GDP), while simultaneously decreasing the undesirable output (i.e., CO_2 emissions) by 17.2%. It is quite interesting to note the difference between Annex I and non-Annex I countries in terms of their efficiency performance (Annex I: 0.9343 vs. non-Annex I: 0.8596) with respect to their group-specific frontier. This difference is significant over the period 1995–2011 (Pillai's Trace $(V) = 0.4$, $F(16,\ 86) = 3.58,\ \ p < 0.01$). In addition, there is a considerable difference in the performance of Annex I and non-Annex I countries with respect to the metafrontier (Annex I: 0.8785 vs. non-Annex I: 0.7970). Meta-efficiency scores of Annex I and non-Annex I countries are expected to drop as the sample size increases. Banker (1993) and Banker and Natarajan (2011) have proven an inverse relationship between sample size and DEA efficiency estimators. Unlike productive efficiencies, the technology gaps of Annex I (i.e., 0.0608) and non-Annex I (i.e., 0.0685) countries are not significantly different over the review period (Pillai's Trace $(V) = 0.168$, $F(16,\ 86) = 1.09,\ \ p > 0.05$).

We begin by examining the estimated productive efficiency and technology gap values for Annex I countries. Drawing on Table A4, which appears in the Electronic Supplement, it is clear that countries such as France (FRA), Germany (GER), Switzerland (CHE), Ireland (IRL), Turkey (TUR), the United Kingdom (UK), and the United States (USA) have the highest productive efficiency scores, equal to unity, over the entire period 1995–2011 (the champions group). By contrast, Belarus (BLR) (i.e., 0.7275), Bulgaria (BUL) (i.e., 0.7324), Hungary (HUN) (i.e., 0.7774), Czech Republic (CZE) (i.e., 0.7892), Croatia (CRO) (i.e., 0.7960) and Estonia (EST) (i.e., 0.7998) perform worst (the laggards group). Furthermore, examining the efficiency scores with respect to the meta-technology (Table A5 in the Electronic Supplement), France (FRA), Ireland (IRL), Italy (ITA), Japan (JAP), Malta (MAL), Norway (NOR), Turkey (TUR), the United Kingdom (UK), and the United States (USA) have technology gaps with zero values. In contrast, countries such as Ukraine (UKR) (i.e., 0.2969), Romania (ROM) (i.e., 0.2726), Latvia (LAT) (i.e., 0.2366), Lithuania (LTU) (i.e., 0.2216), Poland (POL) (i.e., 0.2122), Slovakia (SVK) (i.e., 0.2105) and Portugal (POR) (i.e., 0.2036) have the worst performance among the Annex I countries, suggesting that significant knowledge spillover effects do not occur for country-specific technologies. Interestingly, Germany (GER) is a champion under the Annex I frontier but also has a technology gap of 0.0124, suggesting allocative inefficiency.

Shifting attention to the non-Annex I technological frontier (Table A6 in the Electronic Supplement), Armenia (ARM), China (CHN), Egypt (EGY), Hong Kong (HK), India (IND), Kirgizstan (KGZ),

Table 2
Summary of group-specific and meta-technology outcomes (1995–2011).

Groups	Group-specific efficiency		Meta-technology efficiency		Technology gap	
	Mean	St. deviation	Mean	St. deviation	Mean	St. deviation
Annex I	0.9343	0.0876	0.8785	0.1073	0.0608	0.0937
Non-Annex I	0.8596	0.1266	0.7970	0.1212	0.0685	0.0850
All	–	–	0.8279	0.1226	–	–

Cambodia (KHM), Mexico (MEX), FYR Macedonia (FYR), Mozambique (MOZ), Qatar (QAT), and Sudan (SUD) are assigned productive efficiency scores equal to unity over the entire period 1995–2011. Interestingly, only six of the 64 (6.02%) non-Annex I countries diachronically (1995–2011) define the metafrontier. These countries are: Hong Kong (HK), India (IND), Cambodia (KHM), Mozambique (MOZ), Qatar (QAT), and Sudan (SUD). The remaining group-efficient non-Annex I countries—i.e., Armenia (ARM): 0 times meta-efficient, China (CHN): 1 time meta-efficient, Egypt (EGY): 9 times meta-efficient, Kirgizstan (KGZ): 9 times meta-efficient, Mexico (MEX): 1 time meta-efficient, and FYR Macedonia (FYR): 0 times meta-efficient—underperform significantly. Allocative inefficiencies are more common in non-Annex I countries than in Annex I countries. In particular, two of the group-specific efficient countries (i.e., Armenia (ARM) and Mexico (MEX)) have technology gap values among the highest in their cluster (i.e., ARM: 0.2494, MEX: 0.1746) (Table A7 in the Electronic Supplement). These values remain high throughout the review period. The cases of China (CHN) and Cambodia (KHM), where allocative efficiencies are present, differ from those of Armenia and Mexico as their technology gaps become infinitesimal towards the end of the review period.

The GDDF model, used for measuring group-specific efficiency, meta-efficiency and technology gaps, is regarded as appropriate for handling within-group heterogeneity. Tables A8 and A9 in the Electronic Supplement present (in the first column) the Annex I and non-Annex I countries, respectively, that appear more often than any other country within their group as benchmarks (the value in the grey-shaded lines next to the name of the benchmark country is the number of times this country dominates the group-specific inefficient countries). The second column of Tables A8 and A9 displays the dominated countries affected mostly by the benchmarks (the weights in the seventh column show the significance of the benchmark countries for the optimization of the productive efficiency of the dominated countries). In these two tables, we used the desirable (i.e., GDP) and undesirable (i.e., CO_2 emissions) outputs to justify the appropriateness in handling within-group heterogeneity of the GDDF model. The values of these two variables were classified in quartiles.

Based on Tables A8 and A9, we find that the benchmark countries' GDP and CO_2 emissions are classified in quartiles similar to those of the dominated countries. Therefore, the criterion of homogeneity applies to within-group benchmarks and the dominated countries. For instance, in Table A8, Norway (NOR), which appears 407 times as a benchmark, is classified in Q3 and Q1 based on its GDP and CO_2 emissions, respectively. The countries dominated by Norway, such as Australia (AUS), Austria (AUT) and Belgium (BEL), have GDPs classified in Q4, Q3 and Q3, respectively. Considering CO_2 emissions, where Norway lies within Q1, the dominated countries are classified into higher quartiles (i.e., Q3 and Q4). This classification is valid as the main priority of environmental efficiency measurement, and particularly climate change treaties, such as the Kyoto Protocol, is the reduction/minimization of CO_2 emissions. The GDDF defines benchmark countries with CO_2 emissions classified in a lower quartile than that of the dominated countries. Therefore, countries of similar size (GDP is a proxy for each country's size) are grouped together, and benchmark countries are mostly those with a value of undesirable output lower than that reported by the dominated countries.

The time evolution of the productive efficiency scores for the overall sample, using the corresponding kernel densities (see Fig. 2c) shows a process of continuous and quite significant divergence in 2011 only. This is reflected in the increased deviation of the distribution. This result provides valuable information on the impact of the Kyoto protocol on environmental performance, because 2011 is only one year from its expiration. On the other hand, there is a small, but noticeable deterioration in 2005, the year of the Kyoto transition period. The corresponding time evolution of the Annex I countries (Fig. 2a) reveals that, although the overall picture is quite similar to that of the overall sample, there were significant increases in the productive efficiency scores during the period. Fig. 2b shows the time evolution of the productive efficiency scores of the non-Annex I group. This distribution remains almost steady with no apparent divergence or convergence processes.

A statistically significant positive impact of the Kyoto Agreement, signed in 1997, on the environmental performance both of Annex I and non-Annex I countries is presented in expression (18) and shown in Fig. 3. From 1995 to 1997, a decrease in mean efficiency is not statistically significant (expression (17)).

For the period 1995-1997, the mean environmental efficiency is expressed as follows:

$$\widehat{M.Eff.} = 0.8242^{**} - 19.34 \times 10^{-4} t_1 \tag{17}$$

$$**p < 0.01,\ R^2 = 0.599,\ adjR^2 = 0.399,\ F_{stat} = 2.988$$

where $M.Eff.$ stands for mean efficiency and t_1 stands for time using a coding scheme applied to the period 1995–1997 (i.e. 1995: "0", 1996: "1" and 1997: "2").

For the remaining years of the review period (i.e. 1998–2011), starting from the year after the adoption of the Kyoto Protocol, the mean efficiency is estimated as follows:

$$\widehat{M.Eff.} = 0.8070^{**} + 22.91 \times 10^{-4**} t_2 \tag{18}$$

$$**p < 0.01,\ R^2 = 0.864,\ adjR^2 = 0.851,\ F_{stat} = 69.633^{**}$$

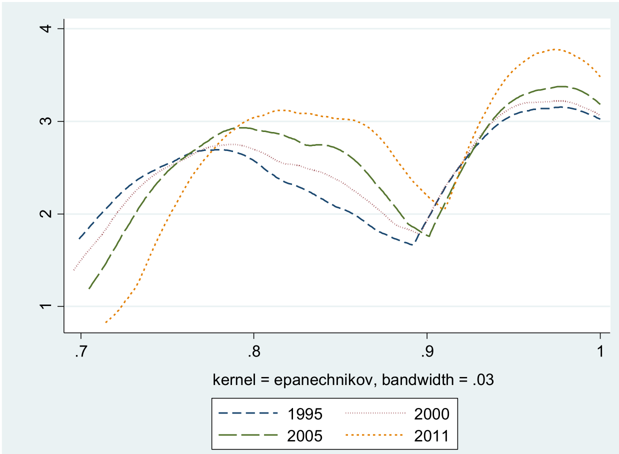
where t_2 stands for time using a coding scheme applied to the period 1998–2011 (i.e. 1998: "0", 1999: "1", 2000: "2", ..., 2011: "13").

In our analysis, we take into account mean efficiencies for each year of the review period as they are the maximum likelihood estimators (MLE) of the parameter (μ_t) (a formal mathematical analysis of the MLE appears in the Appendix).

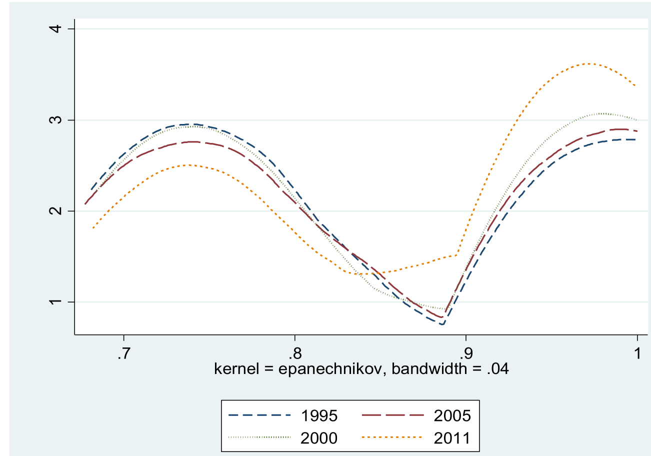
Focusing on the environmental efficiency of Annex I and non-Annex I countries separately, a significant improvement has been made from the year after the Kyoto Protocol entered into force (i.e. 2006). More specifically, the regression model expressing the environmental efficiency of the Annex I countries over the review period is as follows:

$$\widehat{M.Eff.} = 0.9381^{**} - 3.573 \times 10^{-4*} t + 5.467 \times 10^{-4**} Dt \tag{19}$$

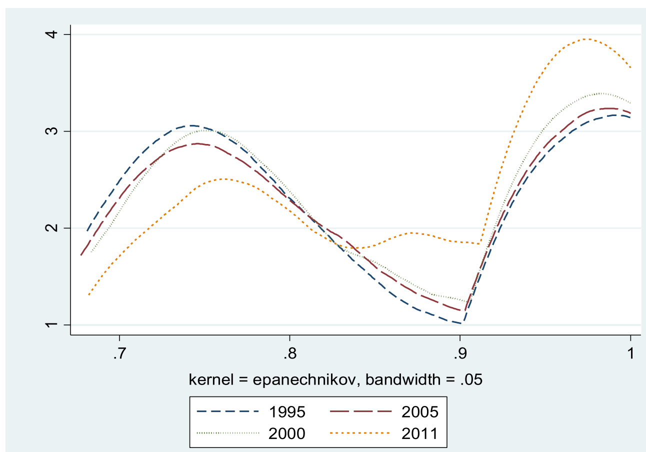
$$**p < 0.01, *p < 0.05,\ R^2 = 0.820,\ adjR^2 = 0.793,$$
$$F_{stat} = 29.698^{**}$$



a. Annex I countries



b. Non-Annex I countries



c. All countries

Fig. 2. Kernel densities of the productive efficiency for Annex I, non-Annex I and all countries groups in 1995, 2000, 2005 and 2011.

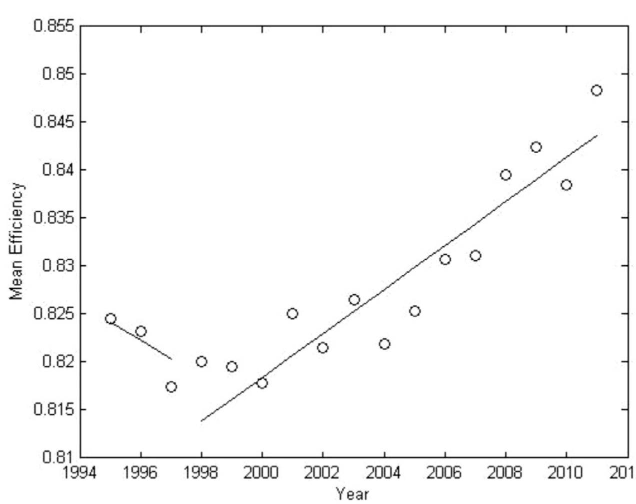


Fig. 3. Mean efficiencies of Annex I and non-Annex I countries.

where t stands for time using a coding scheme applied to the period 1995–2011 (i.e. 1995: "0", 1996: "1", 1997: "2", ..., 2011: "16"), Dt is the interaction between the dummy variable D, where $D = \begin{cases} 0, & year \leq 2005 \\ 1, & year \geq 2006 \end{cases}$ and time t.

For $D = 0$, the regression model (19) is written as follows:

$$\widehat{M.Eff.} = 0.9381 - 3.573 \times 10^{-4} t \tag{20}$$

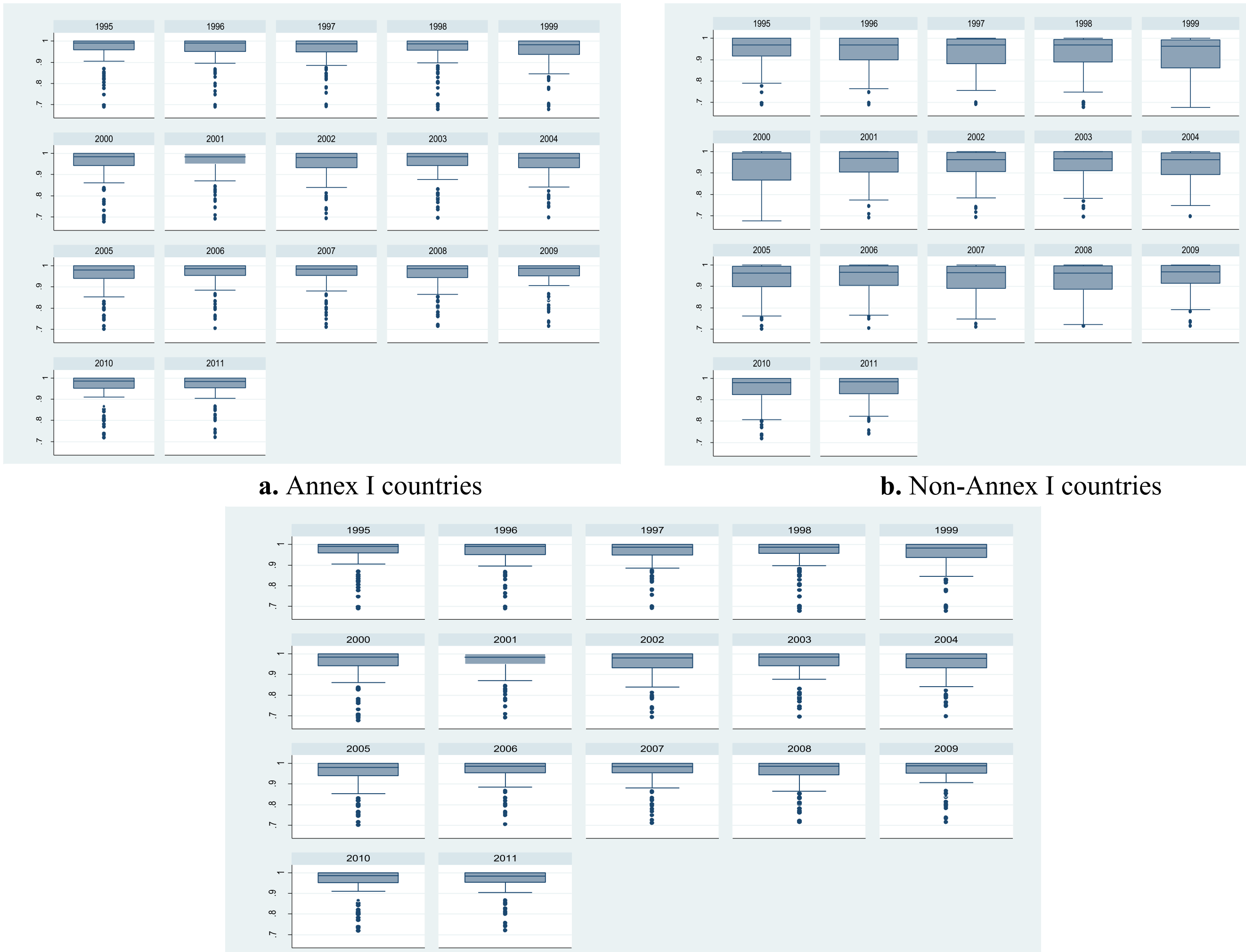
and for $D = 1$, the regression model (19) reads:

$$\widehat{M.Eff.} = 0.9381 + 1.894 \times 10^{-4} t \tag{21}$$

The decline in Annex I countries' environmental efficiency from the beginning of the review period until 2005 is mainly due to the compound annual growth rate in capital stock (input) by 2.68%. This is the highest among the rates of the variables incorporated in the GDDF model. At the same time (1995–2005), the undesirable output CO_2 emissions (undesirable output) increased by 0.76% on average. The improvement of the environmental efficiency of Annex I countries from 2006 until 2011 reflects the positive effect of the adoption of the Kyoto Protocol. For instance, Annex I countries presented a reduction in CO_2 emissions by 0.61% on average for the period 2006–2011. It should be noted that the environmental efficiency improvement was also explained by the decrease in energy consumption (input) from 2008 onward (CAGR 2008–2011: −1.43%), which is related to the global financial crisis.

In the case of the non-Annex I countries, the mean environmental efficiency had been on the rise before the Kyoto Agreement became effective. The regression model (22) expresses the variability of the environmental efficiency of this particular group of countries.

$$\widehat{M.Eff.} = 0.8489^{**} + 10.13 \times 10^{-4**} t + 5.994 \times 10^{-4*} Dt \tag{22}$$



a. Annex I countries **b.** Non-Annex I countries

c. All countries

Fig. 4. Box-plot of metatecnology ratios for Annex I, non-Annex I and all countries groups.

$$**p < 0.01, *p < 0.05, \; R^2 = 0.865,$$
$$adj\,R^2 = 0.846, F_{stat} = 44.914^{**}$$

where the dummy variable $D = \begin{cases} 0, & year \leq 2006 \\ 1, & year \geq 2007 \end{cases}$

For $D = 0$, the regression model (22) is written as follows:

$$\widehat{M.Eff.} = 0.8489 + 10.13 \times 10^{-4} t \tag{23}$$

and for $D = 1$, the regression model (23) becomes:

$$\widehat{M.Eff.} = 0.8489 + 16.124 \times 10^{-4} t \tag{24}$$

Taking into account regression models (23) and (24), improvement in the environmental efficiency of the non-Annex I countries speeds up from 2007 onward. The main reason behind this acceleration is the decrease in CO_2 emissions by 5.35% on average from 2007 until 2011. Unlike the Annex I countries, the energy consumption in non-Annex I countries increased after the global financial crisis (2008–2011) by 5.27% on average.

Finally, the box plots of the diachronic performance of the meta-technology ratios provide additional insight into the distributions of the Annex I countries, non-Annex I countries, and the overall sample. Fig. 4c shows the box plot of the estimated meta-technology ratios for the overall sample. It is evident that meta-technology ratios and their deviations are diachronically constant, with no significant fluctuations. In addition, Annex I countries yield the best average and variance of meta-technology ratios, with a distribution skewed to the right (see Fig. 4a). Moreover, the meta-technology ratios decrease slightly in the 2002–2005 period, but exhibit a drastic increase between 2005 and 2011. Fig. 4b shows the pattern for the non-Annex I meta-technology ratio performance. More specifically, between 1995 and 2001, technology gaps remain quite large, followed by a significant decrease between 2002 and 2008. Then, between 2009 and 2011, a considerable increase emerges. Fig. 4c shows a similar trend for the overall sample meta-technology ratio distribution.

5.2. Stochastic Kernel of Annex I and non-Annex I technology gaps

The stochastic kernel (Quah, 1996a, 1997) resulted from the need to substitute discrete transition matrices. In this way, stochastic kernels can be achieved by estimating the density function of a distribution over a given period (e.g., $t + \rho$), conditioned on the values corresponding to a previous period (e.g., t).

We examine the convergence–divergence hypothesis for technology gaps. The stochastic kernel in Fig. 5 shows how countries' technological gaps evolve between 1995 and 2011. Over the 17-year period, three peaks appear. Each peak reflects a comparatively substantial number of observed transitions from one part of the

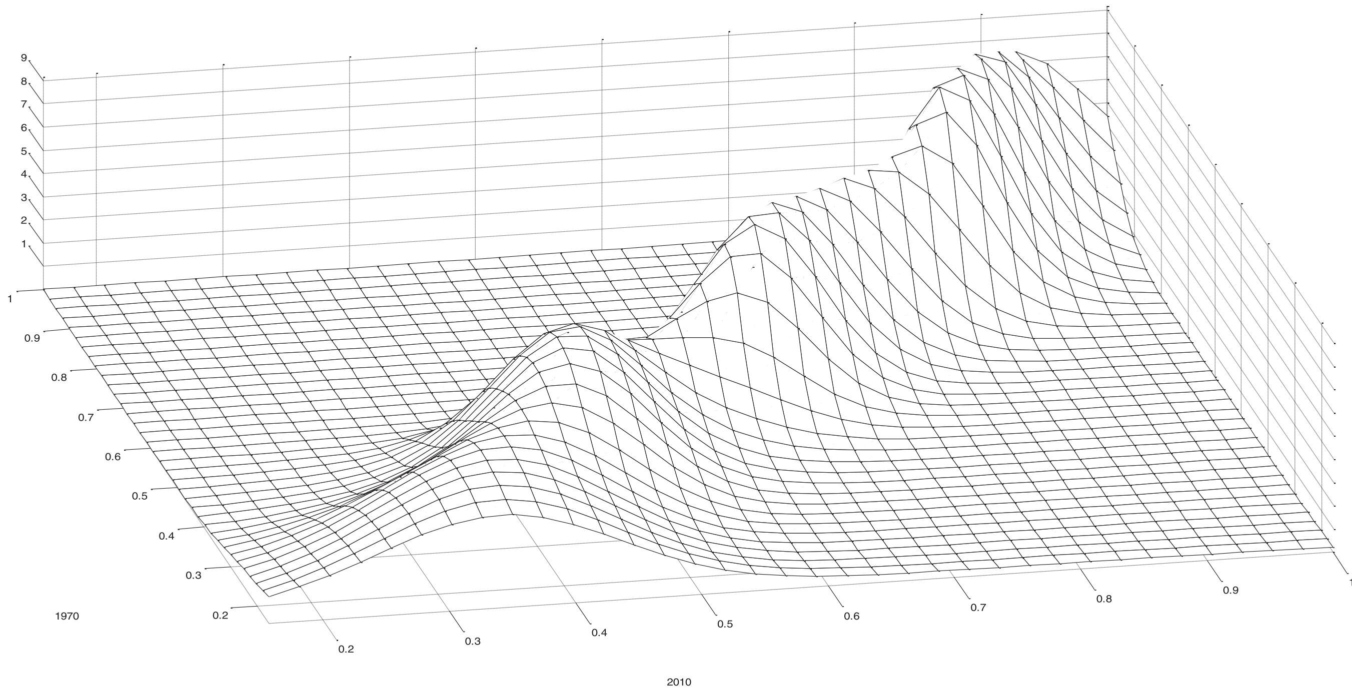


Fig. 5. Stochastic kernel of the distribution of technology gaps.

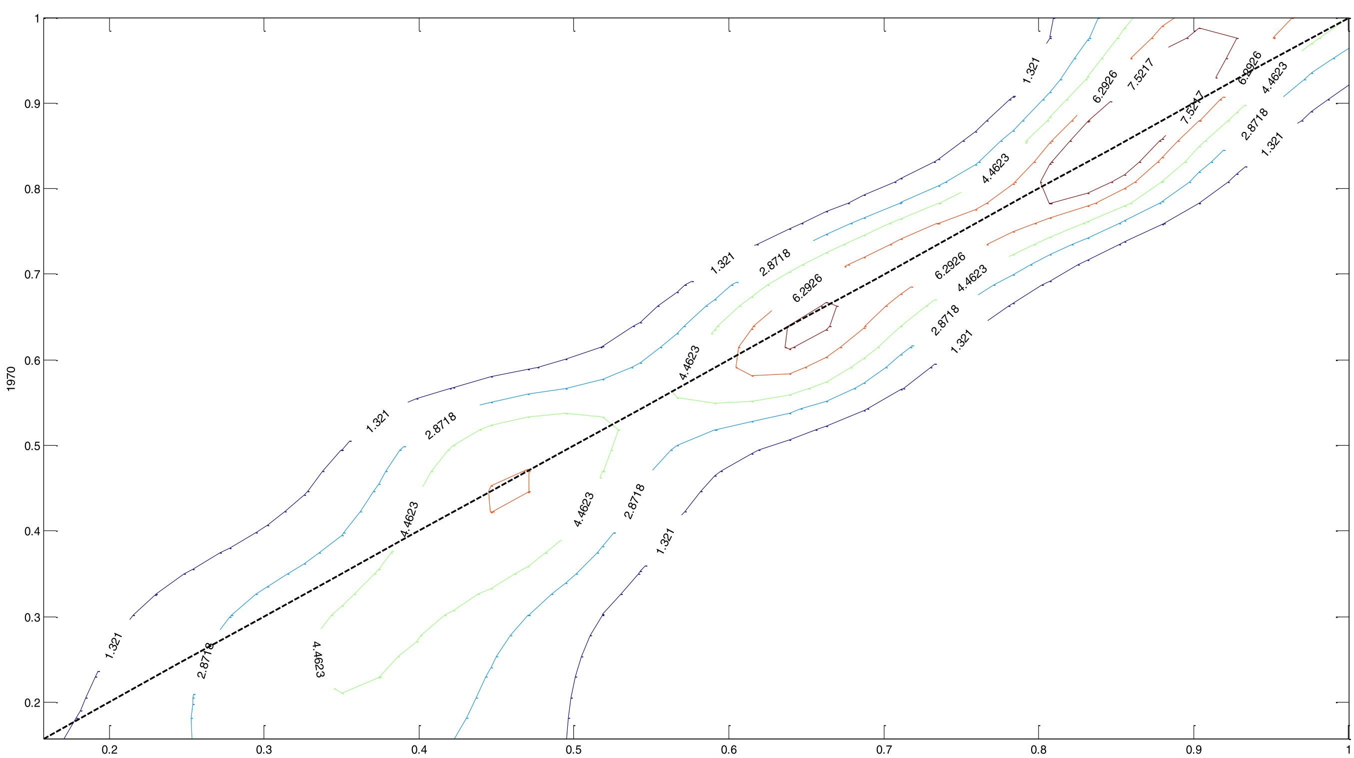


Fig. 6. Contour plot of the distribution of technology gaps.

distribution to another, with a constant point on the x-axis. We can understand the estimated distribution of technology gaps in 2011 in relation to its initial level in 1995. A large portion of the probability mass is concentrated along the 45° diagonal, while the three peaks along the diagonal indicate individual convergence clubs for all 103 countries. More specifically, there are two local maxima in the low and the high technological gaps, and a third in the middle of relative gaps.

Considering the corresponding contour plot in Fig. 6, we find that during the examined period, countries have a low probability of changing their relative position within a year in terms of technological gaps, suggesting that the mobility is low. The three peaks of the technological gaps directly link productivity differentials and the technology structure. This could be explained in terms of factor accumulation deformations, factor price changes that induce the introduction of new technologies (Binswanger et al., 1978),

and localized technological change (Antonelli, 2006; Mulder and De Groot, 2012). Factor accumulation distortions (Easterly & Levine, 2001) of the examined countries in both physical and human capital terms could be important to facilitate the objective of creating the three clubs. For instance, physical capital investment may embody new energy-saving technologies to help in catching up with the frontier, but this is not the case for all countries.

6. Conclusions

Addressing the problems related to climate change and GHGs emissions being released into the environment calls for a better understanding of the patterns of CO_2 emissions and country efficiency performance over time. The Kyoto Protocol, which imposes emissions reduction targets on industrialized countries, has been celebrated as a milestone in climate protection and mitigation for the world community. In this study, we apply a generalized efficiency measure of a directional distance function that allows the directional vector to be independent of the length, under a metafrontier framework. However, we emphasize the construction of a best practice metafrontier production function that allows a comparison of two individual frontiers (Annex I and non-Annex I countries) with different technological regimes.

We find that the Kyoto Protocol has a statistically significant positive impact on the environmental performance both of Annex I and non-Annex I countries. Furthermore, on average, countries in the Annex I group achieved the highest values of productive efficiency and meta-efficiency performance. Among the individual countries, France, Germany, Switzerland, Ireland, Turkey, the United Kingdom and the United States perform best in their group-specific frontier. In addition, Armenia, China, Egypt, Hong Kong, India, Kirgizstan, Cambodia, Mexico, FYR Macedonia, Mozambique, Qatar and Sudan report the same result among the non-Annex I countries. It is evident from our analysis that the environmental performance of non-Annex I countries converges to that of the Annex I countries.

Moreover, the results with respect to technological gaps show a relatively significant difference between the two groups. These differences do not change over time, and exhibit different behaviors in the two clusters. The significantly different behavior of the two clusters, in terms of technological gaps, could depend strongly on differences in their local capabilities and on technological and environmental spillovers from the metafrontier production function. The causes of the different behaviors of the two frontiers warrant further investigation.

We also investigated the convergence hypothesis for technological gaps, showing the significant role of spillovers and their inner flows, for each country and for the two groups. Furthermore, it is related to general factors, such as national policies, levels of technology, ambiguity in the role of internationalization, and lax regulation.

Finally, note that the results of our study are dependent on the countries included in the sample and the variables used. Further research should extend this study to a greater number of countries and based on a longer period. Moreover, it would be interesting to investigate the drivers responsible for diverse groups' behavior, taking into account their environmental performance and technology gap characteristics.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2018.09.004.

Appendix

Proof. The maximum likelihood estimator of the parameter mean (μ_t) equals to $n^{-1}\sum_{j=1}^{n}\theta_{jt}$ for a set of efficiency scores $\Theta_t = (\theta_{jt}),\ j = 1,\dots,n$ and $t = 0,\dots,\kappa$.

The likelihood function (L) of the two parameters, mean (μ_t) and standard deviation (σ_t), for a set of efficiency scores $\Theta_t = (\theta_{jt}),\ j = 1,\dots,n$ is as follows:

$$\begin{aligned} L\left(\mu_t,\, \sigma_t^2 \middle| \Theta_t\right) &= \prod\nolimits_{j=1}^{n} f\left(\theta_{jt} \middle| \mu_t, \sigma_t^2\right) \\ &= \prod\nolimits_{j=1}^{n} \left\{ \frac{1}{\sigma_t\sqrt{2\pi}} exp\left(-\frac{1}{2\sigma_t^2}\left(\theta_{jt}-\mu_t\right)^2\right)\right\} \\ &= \frac{1}{\sigma_t^n\left(\sqrt{2\pi}\right)^n} exp\left(-\frac{1}{2\sigma_t^2}\sum\nolimits_{j=1}^{n}\left(\theta_{jt}-\mu_t\right)^2\right) \end{aligned}$$

The maximum likelihood estimators (MLE) $\widehat{\mu_t}$ and $\widehat{\sigma_t}$ of the parameters μ_t and σ_t, respectively, satisfy both the first and second order conditions:

$$\frac{\partial logL\left(\hat{\mu}_t,\, \hat{\sigma}_t^2 \middle| \Theta_t\right)}{\partial \mu_t} = \frac{\partial logL\left(\hat{\mu}_t,\, \hat{\sigma}_t^2 \middle| \Theta_t\right)}{\partial \sigma_t} = 0$$

$$\text{and } \frac{\partial^2 logL\left(\hat{\mu}_t,\, \hat{\sigma}_t^2 \middle| \Theta_t\right)}{\partial \mu_t^2} < 0$$

In addition, the determinant of the Hessian matrix is:

$$\begin{vmatrix} \dfrac{\partial^2 logL(\hat{\mu}_t, \hat{\sigma}_t^2|\Theta_t)}{\partial \mu_t^2} & \dfrac{\partial^2 logL(\hat{\mu}_t, \hat{\sigma}_t^2|\Theta_t)}{\partial \mu_t \partial \sigma_t} \\ \dfrac{\partial^2 logL(\hat{\mu}_t, \hat{\sigma}_t^2|\Theta_t)}{\partial \mu_t \partial \sigma_t} & \dfrac{\partial^2 logL(\hat{\mu}_t, \hat{\sigma}_t^2|\Theta_t)}{\partial \sigma_t^2} \end{vmatrix} > 0$$

By solving the first-order partial derivatives we obtain:

$$\frac{\partial logL\left(\hat{\mu}_t,\, \hat{\sigma}_t^2 \middle| \Theta_t\right)}{\partial \mu_t} = 0 \Rightarrow \hat{\mu}_t = n^{-1}\sum_{j=1}^{n}\theta_{jt}$$

$$\frac{\partial logL\left(\hat{\mu}_t,\, \hat{\sigma}_t^2 \middle| \Theta_t\right)}{\partial \sigma_t} = 0 \Rightarrow \hat{\sigma}_t^2 = n^{-1}\sum_{j=1}^{n}\left(\theta_{jt}-\hat{\mu}_t\right)^2$$

The second-order partial derivative for μ_t leads to:

$$\frac{\partial^2 logL\left(\hat{\mu}_t,\, \hat{\sigma}_t^2 \middle| \Theta_t\right)}{\partial \mu_t^2} = -\frac{n}{\hat{\sigma}_t^2} \leq\ 0 \text{ and } \begin{vmatrix} -\dfrac{n}{\hat{\sigma}_t^2} & 0 \\ 0 & -\dfrac{2n}{\hat{\sigma}_t^2} \end{vmatrix} = \frac{2n^2}{\hat{\sigma}_t^2} \geq 0$$

Thus, $\hat{\mu}_t = n^{-1}\sum_{j=1}^{n}\theta_{jt}$ is the MLE of μ_t. □

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